EFFECTIVE COLOR CORRECTION VIA CHROMATICITY ADJUSTMENT AND LEAST SQUARE APPROXIMATION

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ABSTRACT

According to the observation that an image under the canonical light has a nearly neutral chromaticity distribution, an efficient three-step color correction approach is proposed: First, a preliminary color-corrected image is generated by linearly shifting the chromaticity distribution of an input image towards the neutral point. Then, a least square approximation formulation is presented to derive the illuminant color from the preliminary color-corrected image. Finally, based on the derived illuminant color and the Von Kries model, a refined color-corrected image can be obtained. From the experimental results on the widely-used SFU image dataset, the proposed approach could achieve comparable or even better performances against other well-known methods. In addition, several web images are examined to further demonstrate the effectiveness of our approach.

Index Terms— Illuminant estimation, Relative Neutral Region, Least square approximation

1. INTRODUCTION

With the fast development of technology, taking pictures has gradually become a common activity in our daily lives. The pixel values captured in an image, however, may drastically vary under different illuminant colors, and hence cannot faithfully display the genuine colors of a scene. This problem not only degrades the image quality, but also makes the subsequent applications such as object recognition more challenging. Therefore, how to achieve color constancy [1] under varied illuminant colors has attracted critical attention in image processing and computer vision.

There are generally two classes of color constancy methods: One aims at an illuminant-invariant image representation [2], [3]; the other seeks to calibrate the color deviation of an image, also called *color correction* in the existing literatures [4]-[9]. This paper mainly focuses on the second category.

In the previous work of color correction, the illuminant color is always estimated at first for subsequent color transformation (e.g., via the Von Kries model [10]). Unfortunately, illuminant estimation has been proved as an ill-posed problem [1]; therefore, all the techniques to achieve it rely on specific assumptions of the image properties [1] such as the restricted gamuts, the color distribution, and the possible light sources in an image. These assumptions, however, are easily violated in real world images, thus resulting in poor illuminant estimation. To alleviate the above defects, we propose a simple yet effective color correction algorithm, where the illuminant color is estimated through a reversed fashion (as illustrated in Fig. 1).

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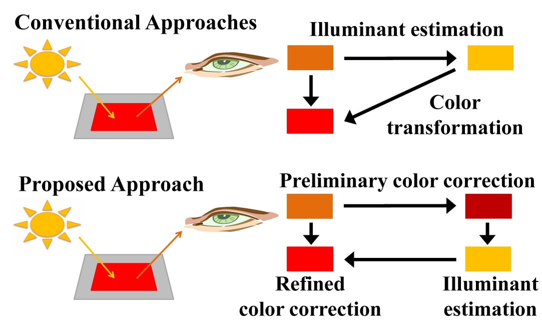

Fig.1. The illustration of the proposed method: Given an observed orange image (whose real color is red), conventional color correction methods first perform illuminant estimation (yellow), and then calibrate the deviated image color via a color transformation model. Our approach, on the other hand, *directly creates a preliminary color-corrected image* (*dark red*)*, which is utilized to calculate the illuminant color through a least square formulation.* The estimated illuminant is then fed into the color transformation model to obtain the refined color-corrected result.

Our algorithm is based on the observation summarized in Fig. 2: *An image under the canonical light (i.e. white light) has a nearly neutral chromaticity distribution* (on the a^*b^* plane of the $L^*a^*b^*$ color space [11]). To attain this property in an image under the non-canonical light, we linearly shift the chromaticity distribution of that image towards the neutral point ($a^*= 0$, $b^*= 0$), leading to a preliminary color-corrected image that is robust against varied illuminant colors. Unfortunately, the constraint brought by the linear shift operation — *the chromaticity distribution of the corrected image is just a globally shifted version of the input image* — is not satisfied in general cases (as be mentioned in 3.3).

In order to release the constraint, a *least square approximation formulation* is presented to derive the illuminant color from the preliminary color-corrected image. The estimated illuminant color is then fed into the standard Von Kries model to generate the refined color-corrected image. Since the Von Kries model has been claimed and examined as a suitable model for calibrating the image color based on the estimated illuminant color [1], the resulting color-corrected image would be more plausible than the one achieved by direct chromaticity shifting. Experimental results on the benchmark SFU image set and several web images (under the non-canonical light) demonstrate the effectiveness of the proposed approach on the illuminant estimation and color correction tasks. The remainder of this paper is organized as follows: Section 2 reviews the previous work of color correction, and Section 3 presents the details of our proposed method. The experiments and the conclusion are included in Sections 4 and 5.

2. RELATED WORK

Algorithms of color correction generally consist of two steps: The first step estimates the illuminant color from the input image; the second step transforms the deviated image color into the authentic color according to the estimated illuminant. Among all kinds of color transformation models, the Von Kries model [10] has become the standard one in the literature; hence, *the performance of color correction is usually measured by the accuracy of illuminant estimation.* In the following, several representative illuminant estimation algorithms are reviewed.

In [4], Land *et al.* proposed the most well-known assumption of illuminant estimation, the white patch assumption, which supposes the existence of highlight patches in a scene that totally reflect the illuminant. The max-RGB algorithm [4], a practical implementation of Land's assumption, then takes the maximum intensities in the color channels as the illuminant color components.

The general gray world hypothesis [5] is according to another assumption: The *p*th-Minkowsky norm of a scene after local smoothing is achromatic. In other words, the normalized *p*th-Minkowsky norms of all pixels in each color channel could be seen as the illuminant color. Slightly different from the general gray world hypothesis, the gray edge hypothesis [5] conjectures that the *p*th-Minkowsky norm of the derivatives (computed in an image) is achromatic; hence, it takes the normalized *p*th-Minkowsky norms over all derivative values in each color channel to be the illuminant.

Based on the assumption that only a limited number of colors can be observed from a given illuminant source, the gamut mapping method [6] and its improvements [7], [8] attempt to map the input gamut into the canonical gamut, which is learned through a tedious process. The concept of learning is also exploited in the color-by-correlation algorithm [9], which links the possible image colors with possible scene illuminants by a correlation matrix.

3. THE PROPOSED ALGORITHM

In this section, the proposed method is described in detail. In 3.1, we introduce the observations for designing our algorithm; in 3.2, the generating process of the preliminary color-corrected image is described. Finally in 3.3, the least square approximation formulation for illuminant estimation is presented.

3.1. The Key Observations

The observations for designing the proposed approach is as follows: When a scene is pictured under different light sources, the pixel values are affected mainly in the chromaticity parts (a^*, b^* components in the $L^*a^*b^*$ color space) rather than in the lightness part. Moreover, the chromaticity distribution of an image under the canonical light (or an image corrected by the ground truth illuminant) is nearly neutral. These phenomena are shown in Fig. 2.

3.2. Color Correction via Chromaticity Shifting

Based on the two observations mentioned above, a simple color correction approach by *linearly shifting the chromaticity distribution* of an image towards the neutral point ($a^*= 0$, $b^*= 0$) is presented. That is, through shifting the a^*, b^* components of each pixel with certain quantities measured from the chromaticity distribution, the color-corrected image could be achieved. To determine the shifting quantities, a centroid-like point has to be defined for representing the overall chromaticity distribution. In our implementation, we select the median values of a^* and b^* to be

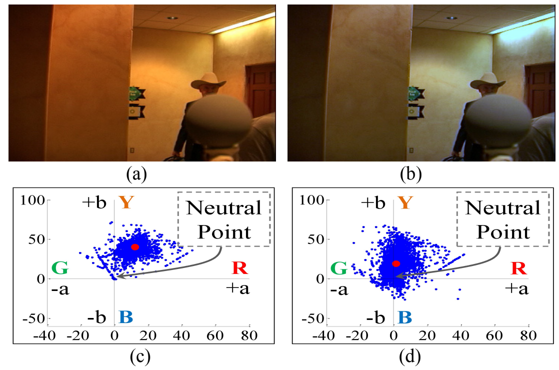

Fig.2. The key observations for designing our color correction algorithm: (a) An example image with the yellowish color deviation. (b) The ground truth image (achieved by the ground truth illuminant). (c)(d) are the chromaticity distributions (blue dots) on the a^* b^* plane of (a)(b); the red point is the median chromaticity. Clearly, an image under the canonical light like (b) has a nearly neutral distribution; i.e. the median chromaticity is very close to the neutral point ($a^*= 0$, $b^*= 0$).

the *representative point* because of its simplicity and robustness against outliers.

Besides the consideration of outliers, it is also shown in [12] that pixel values near the neutral point are more sensitive to the variation of illuminant colors. Namely, these pixels are more informative for color correction. Hence, instead of taking the median values over all the pixels in an image, we propose to discover the *relative neutral region* (*RNR*) at first, and compute the median values of a^* and b^* — denoted as the *representative point* — only from pixels within this region. The definition of RNR is described in Table 1, and in Fig. 3 (b) and (d), the RNR of a yellowish image is illustrated (in gray).

With the *representative point*, the chromaticity distribution of the input image could be linearly shifted by moving this *representative point* to the neutral point, leading to a (preliminary) color-corrected image, as shown in Fig. 3 (c).

3.3. Illuminant Estimation via Least Square Approximation

Color correction via chromaticity shifting apparently alleviates the influence of illuminant colors (as shown in Fig. 3). Nevertheless, the constraint led by this approach — *the chromaticity distribution of the color-corrected image in Fig. 3 (d) is just the globally shifted version of the input image in Fig. 3 (b)* — is generally not satisfied between the input image and the ground truth image (obtained with the ground truth illuminant), which can be seen in Fig. 2 (c) and (d). Namely, the distribution shown in Fig. 2 (d) could not be attained by simply shifting the one in Fig. 2 (c): that is why we call the output of chromaticity shifting the *preliminary* color-corrected image.

Table 1: The definition of the relative neutral region (RNR)

- Denote $\boldsymbol{p}_i$ as the chromaticity vector $\left(a^*(i),\ b^*(i)\right)$ of pixel i.
- Denote $\boldsymbol{m}$ as the maximum chromaticity vector of an image:
$$\boldsymbol{m} = \left(\max_i \left|a^*(i)\right|, \max_i \left|b^*(i)\right|\right)$$
- Denote $\boldsymbol{n}$ as the neutral point (a^*, b^*) = (0, 0).
- Pixel i belongs to the RNR only if $\left\|\boldsymbol{p}_i - \boldsymbol{n}\right\|_2 \le s\left\|\boldsymbol{m} - \boldsymbol{n}\right\|_2$, where s is an adjustable parameter (s = 0.5 in our implementation).

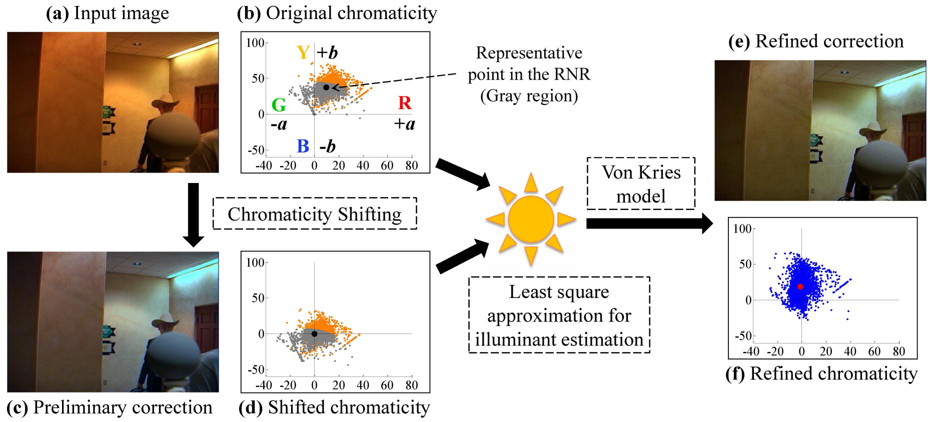

Fig.3. The flowchart of our approach: The three steps are marked with dashed blocks; the *relative neutral region* (RNR) is illustrated in gray in (b) and (d).

To release this constraint, the conventional framework of color correction, *illuminant estimation + color transformation*, is taken into account for refining the color correction result. Specifically, we try to calculate the illuminant color from the preliminary color-corrected image, and then adopt the standard Von Kries model for generating the refined color-corrected image. In our implementation, we model the illuminant estimation process as an approximation problem. Namely, the illuminant color that leads to the color-corrected result (through the Von Kries model) most similar to the preliminary color-corrected image (by the *square error*) is selected.

Denote the canonical and the estimated illuminant colors as $\boldsymbol{e_C}$ and $\boldsymbol{e_E}$, which are both 3-dimensional vectors, the Von Kries model calibrates each color channel j (in the *RGB* space) of the input image individually based on the corresponding illuminant component e_E^j:

$$x_j^*(i) = x_j(i) \times \left(e_C^j / e_E^j \right), j \in \{R, G, B\}, \quad (1)$$

where $x_j(i)$ and $x_j^*(i)$ are the color component j of pixel i in the input and the output images; the canonical illuminant $\boldsymbol{e_C}$ is set as $[1/\sqrt{3}, 1/\sqrt{3}, 1/\sqrt{3}]^T$ in general. Hence, each illuminant component e_E^j can be computed separately via the least square optimization problem below:

$$e_E^j = \arg\min_{e^j} \sum_{i=1}^{N} \left| y_j(i) - x_j(i) \times \left(e_C^j / e^j \right) \right|^2, j \in \{R, G, B\}, \quad (2)$$

where y_j (i) indicates the color element j of pixel i in the preliminary color-corrected image; N represents the number of pixels in the input image. By rewriting $\boldsymbol{x_j}$ and $\boldsymbol{y_j}$ as the N-dimensional vectors recording all the color component j in the input and the preliminary corrected images, e_E^j can be achieved by the following formula:

$$e_E^j = e_C^j \times \left(\boldsymbol{x}_j^T \boldsymbol{y}_j \right)^{-1} \left(\boldsymbol{x}_j^T \boldsymbol{x}_j \right), j \in \{R, G, B\}. \quad (3)$$

With the least square formulation in (2) and the solution in (3), the illuminant color $\boldsymbol{e_E}$ can be derived from the preliminary color-corrected image. In Fig. 3 (e) and (f), the refined color-corrected results via $\boldsymbol{e_E}$ and the Von Kries model are presented. Clearly, the constraint of chromaticity shifting has been effectively released; the refined color-corrected results are much more similar to the ground truth image and chromaticity distribution in Fig. 2 (b), (d).

4. EXPERIMENTAL RESULTS

In this section, the performance of our approach is evaluated on the benchmark SFU real world image set [13] and some web images pictured under different light sources. Several color correction algorithms by first estimating the illuminant color are compared, such as the max-RGB method (MR) [4], the general gray world hypothesis (GGW) [5], the first order and the second order gray edge hypotheses (GE1, GE2) [5]. Because our approach requires no learning phase, the gamut mapping [6]-[8] and the color-by-correlation methods [9] mentioned in Section 2 are not compared. The parameters of GGW, GE1, and GE2 are set based on [5].

Two criteria are used for performance evaluation on illuminant estimation and color correction respectively. First, we measure the discrepancy between the estimated and the ground truth illuminant colors $\boldsymbol{e_E}$ and $\boldsymbol{e_G}$ by the popular angular error d_{angle} [4]:

$$d_{angle} = \cos^{-1}\left(\frac{\mathbf{e}_G \bullet \mathbf{e}_E}{\|\mathbf{e}_G\| \|\mathbf{e}_E\|} \right), \quad (4)$$

where $\|\cdot\|$ means the L_2 norm. Second, we assess the goodness of color correction by calculating the chromaticity differences C_D (on the a^*, b^* components) between the color-corrected images and the ground truth images (obtained by the ground truth illuminants): C_D is measured by the root mean square error.

4.1. Experiments on the SFU Image Database

The SFU image dataset [13], provided with the ground truth illuminant colors, is composed of 15 video clips. Since images within the same video clip have high correlations, we sample the images with the interval of 10 in each clip, resulting in a subset of totally 1128 images for the whole dataset.

The illuminant estimation results on the SFU image subset are shown in Table 2, where the median, mean, and standard deviation (STD) of the angular errors (Unit: degree) are firstly calculated in each video clip, and then averaged over the 15 clips. In this way, the influence of each clip could be balanced. As presented, the proposed approaches (with or without the RNR) outperform other compared methods both in the median and mean angular errors.

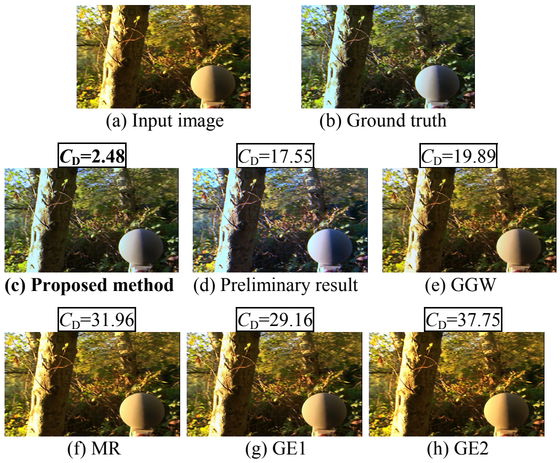

Fig. 4. Color corrected results on an image of the *Deer_Lake* video clip

Besides, the *relative neutral region* (RNR) is indeed helpful to further reduce the angular errors. The color correction performances on the SFU dataset are listed in Table 3, where both the preliminary (via chromaticity shifting only) and the refined results (with illuminant estimation and Von-Kries model) are involved. As shown, our approach (with the RNR and refinement) works better than other algorithms in terms of the median and mean errors on the chromaticity components. And similar to the illuminant estimation results, the errors with the RNR are still lower than the ones without the RNR, justifying the effectiveness of RNR on both the color correction and illuminant estimation tasks. Furthermore, the performance gain achieved by the refinement process (in 3.3) does significantly reduce the color correction error, demonstrating our attempt to release the constraint led by the simple chromaticity shifting method.

In Fig. 4, the color correction results by applying different color correction algorithms on images in the *Deer_Lake* video clip are displayed. As shown, our approach (with the RNR and refinement) can effectively remove the influence of the yellowish illuminant.

4.2. Experiments on Web Images

In this subsection, we take a further step to compare our approach (with refinement and the RNR) to other methods on web images taken under different light sources. Because the web images are usually not provided with the ground truth illuminants as well as the ground truth images, we only show the color-corrected results in Fig. 5. As presented, the proposed approach is more effective than other methods on reducing the influence of illuminant colors.

Table 2: Illuminant estimation performances on the SFU image set

d_{angle}	GGW	MR	GE1	GE2	**Ours** (no RNR)	**Ours** (RNR)
Median	6.76	6.84	6.39	6.45	**6.23**	**6.00**
Mean	7.15	7.73	7.26	7.41	**6.79**	**6.57**
STD	4.24	3.88	4.48	4.82	**4.01**	**3.85**

5. CONCLUSION

In this paper, a simple yet effective color correction algorithm is proposed. By *linearly shifting the chromaticity distribution* of an image towards the neutral point, a preliminary color-corrected result (accompanied by a strong constraint in the chromaticity distribution) could be attained. To release the constraint, we present a *least square approximation formulation* to derive the illuminant color, which is then fed into the Von Kries model for refinement. The experimental results demonstrate the effectiveness of our approach on both illuminant estimation and color correction.

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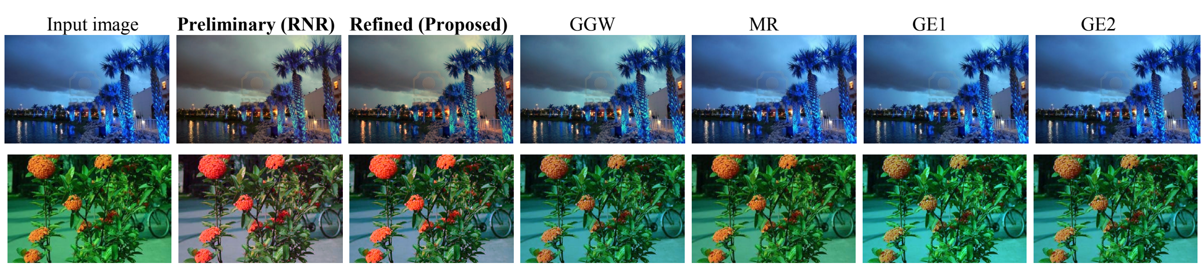

Fig. 5. Color correction results on a *bluish* and a *greenish* web images with different color correction methods.

Table 3: Comparisons of the chromaticity difference (C_D) on the SFU image set

C_D	GGW	MR	GE1	GE2	Preliminary(no RNR)	Preliminary(RNR)	**Refined(no RNR)**	**Refined(RNR)**
Median	7.76	7.76	7.45	7.55	10.30	9.80	**7.51**	**7.25**
Mean	8.31	8.73	8.33	8.68	11.29	10.71	**8.09**	**7.82**
STD	3.99	3.63	4.17	4.55	4.61	4.20	**4.05**	**3.84**

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